

Article

Multi-Case Simulation-Based Scalability Validation of Parallel Assembly Sequence Planning for Sustainable Manufacturing of Large-Scale Wind-Turbine Gearboxes and Complex Products

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Abstract

Efficient assembly planning is increasingly recognized as an important enabler of sustainable manufacturing because it decreases production duration, rework, resource consumption, and operational waste. The assembly of large-scale wind-turbine gearboxes and complex products is characterized by high part counts, heavy and tolerance-critical parts, intricate priority constraints, and significant opportunities for parallel-task execution. This paper presents a multi-case simulation-based experimental performance and scalability validation of these complex products. A scaling-based simulation technique was developed, applying assembly graph parameters, number of tasks, priority edges, integration nodes, priority density, handling complexity, and error risk. The 10 MW wind-turbine gearbox was applied as the calibration baseline and twelve benchmark cases were simulated using Monte-Carlo uncertainty propagation. Outcomes demonstrate that the proposed PASP framework scales consistently across product families, with time decrease fluctuating from 20.4% to 30.3%, cost reductions fluctuating from 9.4% to 18.0%, and quality indices improving from baseline values of 0.87–0.94 to enhanced values of 0.91–0.965. Error decrease remained mainly strong in large wind-turbine assemblies, attaining 85–92% in offshore, hub-pitch, nacelle, generator, and gearbox cases. These outcomes validate the fact that the proposed PASP components are transferable, scalable, and appropriate for sustainable Industry 4.0 complex assembly line systems where cost control, quality, reliability, and productivity must be augmented, simultaneously.

Keywords: sustainable manufacturing; parallel assembly sequence planning; multi-case simulation; scalability validation; Monte-Carlo uncertainty propagation; adaptive scheduling; wind turbine



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1. Introduction

Beyond productivity improvement, assembly planning plays an increasingly important role in sustainable manufacturing and assembly systems [1]. Inefficient assembly sequences may lead to unnecessary machine utilization, prolonged occupation of assembly resources, repeated handling operations, unnecessary energy consumption and increased risk of assembly defects requiring rework [2]. Wind-turbine gearbox manufacturing is

one of the most challenging assembly processes in renewable energy equipment production [3,4]. Environmental and meteorological conditions, including wind speed, temperature, and humidity, influence wind-turbine operation, reliability, and maintenance, while machine-learning approaches demonstrate the value of meteorological data for wind-energy forecasting. Although this study focuses on manufacturing-stage assembly planning, future smart assembly systems should integrate environmental, operational, and real-time sensor data to improve reliability and adaptability [5].

Large-scale gearboxes consist of heavy shafts, ring gears, planetary gear sets, sun gears, bearings, carriers and housing configurations that require assembly in a stringent technical order [3,6]. The challenge becomes more severe as wind-turbine ratings surge from medium-scale onshore machines to 10 MW, 15 MW and bigger offshore platforms [7,8]. Higher-rated power generally increases gearbox size, handling difficulty, incorporation complexity and tolerance sensitivity, making traditional serial assembly line planning inefficient [9–11]. Traditional Assembly Sequence Planning (ASP) often assumes sequential execution of tasks, although huge mechanical products including wind-turbine gearboxes, generators, nacelles, EV powertrains, aerospace modules, battery packs and industrial gearboxes comprise numerous subassemblies that can be assembled in parallel lines [10,12–14]. Parallel Assembly Sequence Planning (PASP) exploits this concurrency by allocating feasible tasks across several assembly lines while respecting precedence, resource, time, cost, quality and integration constraints. PASP, consequently, has a strong prospective of reducing makespan, improving resource use, and improving productivity. The study developed a PASP framework for a 10 MW wind-turbine gearbox, based on four main components:

1. A PASP-TCQ (time, cost and quality) model, which is a hybrid time-, cost- and quality-optimization model with constraints.
2. A PSBFO algorithm based on hybrid particle swarm optimization (PSO) and a bacterial foraging optimization (BFO) method for sequence optimization.
3. The advanced priority relationship algorithm (APRA).
4. Assembly error reduction in parallel assembly sequence planning (PASP).

The results from these studies applied on a 10 MW gearbox show that PSBFO reduced assembly duration from 120 to 100 h and cost from USD 105,000 to USD 94,500, and improved the quality index from 0.89 to 0.93. APRA additionally reduced assembly line duration to 88.8 h, representing a 26%-time reduction. Assembly error reduction applying the PSBFO framework reduced assembly line errors from 50 to 5, representing a 90% error reduction. Although these outcomes validate the framework for the original gearbox case, journal-level contribution requires validating whether the approach is scalable beyond a single product, which is in this case a wind-turbine gear box. Complex industrial systems vary in task count, priority density, number of incorporation points, handling challenges and assembly risk. Therefore, the main objective is to assess whether the proposed PASP techniques remain effective across different product scales and complexity levels. The research questions are the following:

1. How does the PASP framework perform as assembly scale and complexity increase?
2. Do time, cost, quality and error-reduction benefits remain stable across different product families?
3. Which PASP system is the most effective under different scalability conditions?
4. Can the 10 MW gearbox outcomes be generalized to larger wind-turbine assemblies and other complex assembly line systems?

Unlike previous PASP studies that primarily validated a proposed method using a single product or a single wind-turbine gearbox, this study develops and evaluates a multi-case simulation framework for testing scalability across diverse complex-product assembly

systems. The benchmark cases differ in task count, precedence density, integration-node density, component size, handling requirements, tooling intensity, and manufacturing constraints [15,16]. The purpose is, therefore, not only to determine whether PASP improves individual assembly solutions, but also to investigate how product and process complexity influences the magnitude and consistency of those improvements [17,18]. The main contribution of this study is a multi-case, simulation-based scalability assessment of an integrated PASP framework. Rather than proposing an isolated new metaheuristic, the study evaluates the transferability of previously developed PASP components across wind-turbine and complex-product assembly cases with varying technological, integration, handling, and manufacturing complexity. The framework provides a complexity-aware basis for comparing time, cost, quality, error risk, and feasibility under different assembly conditions. The novelty of the present manuscript is not the re-development of those individual methods. Rather, the novelty lies in the following aspects:

1. Multi-case scalability validation: the study evaluates the transferability and scalability of the PASP framework across multiple simulation-based benchmark cases, rather than validating it only for one wind-turbine gearbox.
2. Complexity-aware benchmarking: the study introduces a complexity-driven simulation framework incorporating task count, precedence density, integration nodes, component mass, handling complexity, tooling, tolerance sensitivity, quality requirements, and error risk.
3. Integrated evaluation of PASP components: the work evaluates PASP-TCQ, PSBFO, APRA, and error-aware PSBFO under a common performance framework including time, cost, quality, assembly errors, and manufacturing constraints.
4. Comparison with a recognized multi-objective benchmark algorithm: the revised manuscript includes comparison with NSGA-II to demonstrate the advantages and limitations of the proposed PASP-based optimization framework.
5. Industry 4.0 and Industry 5.0 positioning: the study now explicitly discusses how the framework contributes to Industry 4.0-enabled smart assembly and how it can be extended toward Industry 5.0 through human-centric, sustainable, and resilient manufacturing objectives.

2. Literature Review

2.1. PASP and Sustainable Manufacturing of Intricate Assembly Systems

Assembly sequence planning (ASP) is an important activity in sustainable manufacturing systems because it determines the order in which parts are assembled to attain assembly effectiveness, cost reduction and product-quality enhancement. Traditional ASP methods primarily focus on chronological execution of assembly line tasks where operations are performed in a fixed order, based on priority relationships [19]. Whereas chronological scheduling is appropriate for moderately simple products, it becomes increasingly ineffective for large-scale and intricate products comprising several interdependent parts and subassemblies. PASP developed as an extension of ASP to address shortfalls associated with serial assembly, and enables multiple feasible tasks to be executed concurrently while satisfying priority, resource and integration constraints [20,21]. The ability of PASP to allocate assembly tasks across numerous assembly lines or workstations considerably reduces makespan and improves resource utilization. This benefit is particularly important for intricate engineering systems including wind-turbine gearboxes, automotive powertrains, aerospace engine modules, and industrial robotic systems where part interaction and incorporation requirements are highly intricate [22,23]. Wind-turbine gearboxes present a particularly challenging PASP application because they contain several heavy, tolerance-sensitive, and structurally interrelated parts that must be assembled in strict practical

order [3,8]. The increasing scale of wind-turbine systems from medium-sized onshore turbines to offshore systems beyond 15 MW further increases assembly intricacy, making traditional chronological-planning approaches insufficient. Thus, advanced PASP methods have gained important attention in renewable energy manufacturing systems.

2.2. Optimization Models for PASP

Optimization models in PASP are targeted to minimize assembly duration and cost while sustaining product quality and feasibility constraints. Conventional optimization models often focus on single-objective functions, such as reducing total assembly time or balancing assembly lines; modern assembly systems require multi-objective optimization because assembly line choices instantaneously affect productivity, cost efficiency and product quality [24]. Hybrid optimization models have increasingly been proposed to address this challenge. Multi-objective optimization methods combine several variables and feasibility into integrated decision-making frameworks [20,21]. In wind-turbine gearbox assembly, hybrid time–cost–quality models have shown significant benefits because gearbox assembly involves expensive parts, high handling intricacy and strict quality [25]. Recent research indicates that effective PASP models should integrate priority relationships, resource limitations, integration restrictions, and quality penalties, to ensure realistic assembly line plans. Restriction-based assembly planning methods have further enhanced the ability of PASP systems to handle large-scale products with complex priority structures [26]. Regardless of these advances, several current models remain limited in scalability and adaptability across different product families, inspiring the need for simulation-based scalability validation.

2.3. Metaheuristic Algorithms for Assembly Sequence Optimization

ASP problems are normally recognized as NP-hard optimization problems because the number of possible assembly sequences surges exponentially with product intricacy [27]. Exact optimization methods such as Mixed Integer Linear Programming (MILP) become computationally expensive for large-scale industrial applications, and as a result, metaheuristic algorithms have become widely adopted and popular, due to their flexibility and computational efficiency. PSO, inspired by collective swarm behavior has been widely applied to assembly sequence optimization because of its strong global exploration capabilities [28,29]. PSO efficiently searches solution spaces and recognizes favorable assembly configurations; however, PSO may suffer from early merging and entrapment in local optima, especially in highly constrained assembly systems [30]. BFO has also been applied to PASP, due to its robust local-search and -exploitation capability, simulating bacterial chemotaxis behavior to iteratively improve processes. While BFO improves local optimization performance, its merging speed is often slower than that of PSO, and to overcome the limitations of individual metaheuristics, hybrid algorithms integrating PSO and BFO have gained increasing consideration. The PSBFO algorithm incorporates the global-exploration ability of PSO with the local-refinement ability of BFO, improving and merging accuracy and optimization robustness. Previous research on wind-turbine gearbox assembly established that PSBFO reduced assembly duration, minimized cost, and improved quality, compared with separate PSO and BFO methods [9].

2.4. PASP Machine-Learning Approaches

Current developments in smart manufacturing and Industry 4.0 have enhanced the integration of machine-learning techniques into assembly line planning systems. Traditional PASP methods typically assume static priority relationships which restrict adaptability under varying assembly conditions. Machine learning presents adaptive decision-making ability by continuously learning from past and real-time operational data [31]. Machine-learning models such as random forest, reinforcement learning and predictive analytics

have shown robust potential for refining assembly sequence planning efficiency [32]. These methods support dynamic adjustment of task priorities based on operational performance, quality results and resource availability. APRA represents a machine-learning-enhanced PASP approach that dynamically updates assembly task priorities using random forest prediction models. APRA enhances assembly effectiveness by continuously adjusting priority relationships based on predicted task performance and past operational data. Prior research validated the fact that APRA reduced assembly duration by approximately 26% in a 10 MW wind-turbine gearbox without compromising quality or increasing cost [3].

2.5. Error Reduction in PASP

Assembly errors remain one of the main challenges in multifaceted assembly systems because mistakes in assembly line sequence execution can lead to product downtime, failures and costly maintenance requirements. Wind-turbine gearboxes are predominantly vulnerable to assembly errors, due to their heavy parts, configuration sensitivity, torque precision requirements and integration complexity [33]. Traditional assembly optimization methods largely emphasize productivity and cost reduction while paying inadequate attention to assembly reliability and error minimization. Error-aware optimization frameworks have therefore emerged to explicitly incorporate task-specific error likelihoods and priority violation penalties into assembly planning [34]. Error-aware PSBFO methods incorporate reliability considerations into assembly optimization by minimizing predictable assembly errors while preserving production efficiency. Recent research demonstrated that error-aware PSBFO reduced gearbox assembly errors by approximately 90%, improving assembly line consistency and operational robustness in renewable energy systems [8].

2.6. Industry 4.0 and Industry 5.0 Perspectives in Sustainable Wind-Turbine Assembly

Industry 4.0 emphasizes digitalization, automation, cyber-physical systems, artificial intelligence, industrial Internet of Things, and data-driven decision-making. In contrast, Industry 5.0 extends this technological perspective by emphasizing human-centricity, sustainability, and resilience [35,36]. The proposed PASP framework is mainly aligned with Industry 4.0 because it uses simulation, machine-learning-based priority adaptation, meta-heuristic optimization, and uncertainty analysis, to improve assembly performance [37]. However, the framework also provides a basis for Industry 5.0-oriented development because reduced rework, shorter assembly duration, lower resource consumption, reduced error risk, and safer task allocation can contribute to sustainable and human-centered manufacturing [38]. Table 1 distinguishes Industry 4.0 from Industry 5.0.

Table 1. Comparison between Industry 4.0 and Industry 5.0.

Aspect	Industry 4.0	Industry 5.0	Relevance to This Study
Main focus	Automation, connectivity, cyber-physical systems, IoT, data-driven manufacturing [36]	Human-centric, sustainable, and resilient manufacturing [38]	PASP currently supports Industry 4.0 assembly optimization and can be extended toward Industry 5.0
Main objective	Productivity, flexibility, efficiency, quality [37,39]	Human well-being, sustainability, resilience, and responsible production [40]	Future PASP models should include worker safety, ergonomics, energy, emissions, and disruption resilience
Human role	Monitoring, supervision, and exception management	Human-machine collaboration and operator-centered decision-making [41]	Operator skill, workload, and ergonomic constraints should be included
Digital technologies	IoT, AI, robotics, digital twins, cloud systems	Industry 4.0 technologies combined with collaborative and human-centered systems [35]	APRA, simulation, and optimization provide a foundation for digital assembly planning
Sustainability	Resource efficiency and waste reduction	Life-cycle sustainability, circularity, environmental responsibility	Energy use, rework, and material waste are relevant PASP extensions
Resilience	Flexible connected production	Robust operation under disruptions and uncertainty	Monte-Carlo uncertainty analysis supports an initial resilience perspective

3. Materials and Methods

3.1. Research Framework

The reference case considered in this study is a 10 MW offshore geared wind-turbine drivetrain, with the gearbox assembly used as the calibration baseline. The gearbox includes heavy and tolerance-critical components, such as the housing, planetary carriers, ring gears, sun gears, shafts, bearings, seals, lubrication components, and fastening interfaces. The detailed optimization framework is applied primarily to gearbox- and drivetrain-assembly tasks. Figure 1. Shows the general schematic of the proposed method.

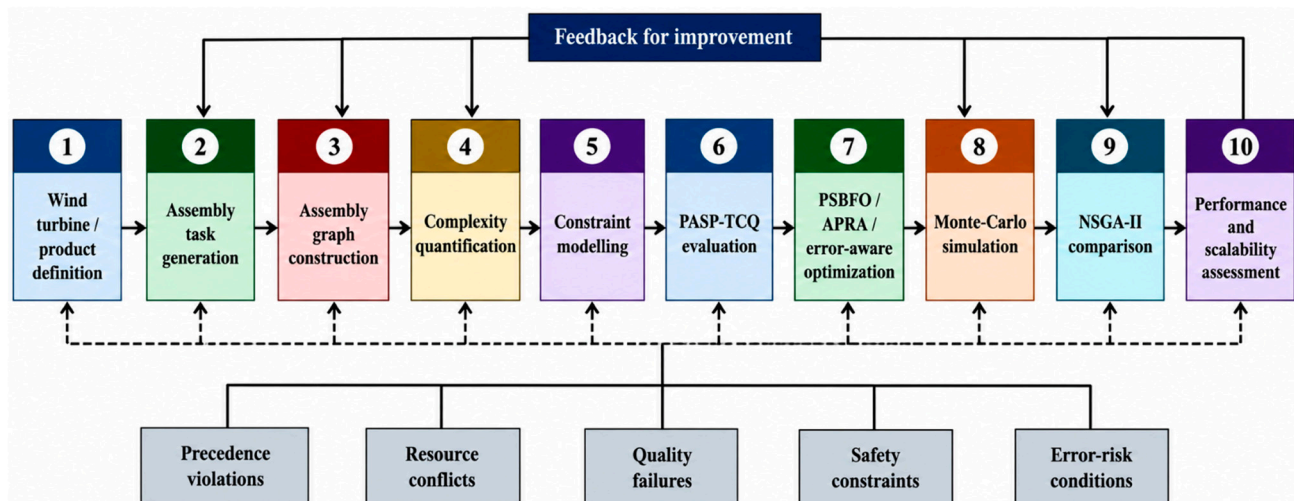


Figure 1. General schematic of the proposed method.

The methodology is based on a simulation-driven scalability validation procedure applying the 10 MW wind-turbine gearbox as the baseline case shown in Figure 2. Other product cases are represented and generated using scaled assembly-graph parameters. Each case is evaluated under baseline planning and optimized PASP planning. The proposed method is designed as a decision-support framework for large-scale assembly planning. It incorporates manufacturing-related constraints that directly affect assembly feasibility. However, detailed upstream fabrication processes, such as casting, forging, gear cutting, heat treatment, blade composite lay-up, and coating, are not explicitly modeled and are identified as an important direction for future work. The performance-indicator mathematical models represent the simulation-based scalability validation for PASP across large-scale industrial assembly systems.

3.2. Assembly Graph Representation

Each product case is represented as a directed assembly graph, as shown in Equation (1):

$$G_j = (N_j, A_j) \quad (1)$$

where

- G_j is the assembly graph of case j .
- N_j is the set of assembly tasks.
- A_j is the set of precedence arcs between tasks.

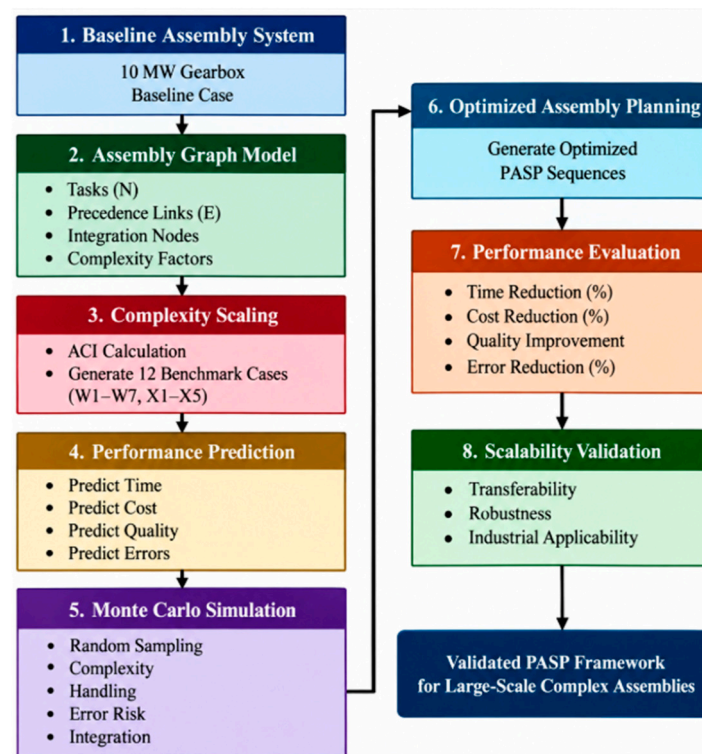


Figure 2. Simulation-based scalability validation for PASP across large scale industrial assembly systems.

The number of tasks is expressed in Equation (2):

$$n_j = |N_j| \quad (2)$$

The number of precedence constraints is expressed in Equation (3):

$$m_j = |A_j| \quad (3)$$

k_j represents the number of integration or merge nodes; integration nodes represent points where independently assembled subassemblies must be joined. The precedence density is defined in Equation (4):

$$d_j = \frac{m_j}{n_j(n_j - 1)} \quad (4)$$

The integration factor is expressed in Equation (5):

$$\kappa_j = \frac{k_j}{n_j} \quad (5)$$

A higher d_j means the assembly has more precedence restrictions, while a higher κ_j indicates more subassembly merging points.

3.3. Normalized Assembly-Complexity Index

To compare cases of different sizes, a normalized assembly-complexity index is defined, relative to the 10 MW gearbox baseline, as expressed in Equation (6):

$$\Omega_j = w_n \left(\frac{n_j}{n_0} \right) + w_d \left(\frac{d_j}{d_0} \right) + w_k \left(\frac{\kappa_j}{\kappa_0} \right) \quad (6)$$

where

- Ω_j is the normalized assembly complexity of case j .
- n_0 , d_0 , and κ_0 are the task count, precedence density, and integration factor of the 10 MW baseline gearbox.
- w_n , w_d , and w_k are weighting coefficients, satisfying Equation (7):

$$w_n + w_d + w_k = 1 \quad (7)$$

In this paper, the complexity index captures three major scalability dimensions:

1. Product size, represented by n_j/n_0 ;
2. Precedence intensity, represented by d_j/d_0 ;
3. Integration difficulty, represented by κ_j/κ_0 .

3.4. Baseline Time- and Cost-Scaling Models

The baseline assembly time for case j is estimated using nonlinear scaling, as expressed in Equation (8):

$$T_j^{\text{base}} = T_0 \cdot \Omega_j^{\alpha_T} \cdot \left(\frac{H_j}{H_0} \right)^{\beta_T} \quad (8)$$

where:

- T_j^{base} is the baseline assembly time for case j .
- T_0 is the baseline time of the 10 MW gearbox.
- H_j is the handling-complexity index for case j .
- H_0 is the handling complexity of the 10 MW gearbox.
- α_T and β_T are time-scaling exponents.

Similarly, the baseline cost is expressed in Equation (9):

$$C_j^{\text{base}} = C_0 \cdot \Omega_j^{\alpha_C} \cdot \left(\frac{H_j}{H_0} \right)^{\beta_C} \quad (9)$$

where

- C_j^{base} is the baseline cost for case j .
- C_0 is the baseline cost of the 10 MW gearbox.
- α_C and β_C are cost-scaling exponents.

The handling-complexity index H_j captures factors such as lifting requirements, tooling intensity, fixture complexity, component mass, and manual-handling difficulty.

3.5. Monte-Carlo Simulation Protocol

To account for uncertainty, scaling parameters were sampled using Monte-Carlo simulation. The Monte-Carlo simulation results demonstrate that the proposed PASP framework remains robust under uncertainty in processing time, handling time, inspection time, assembly-error probability, and rework duration. Using 10,000 simulation trials, the stochastic evaluation provides stable estimates of assembly performance, with the mean performance indicators converging within the specified 0.5% convergence criterion. The simulation results indicate that the uncertainty in individual assembly activities does not materially change the overall performance trends observed in the deterministic analysis. The proposed framework maintains feasible assembly sequences, while providing improved assembly-time performance, reduced error risk, and stable quality outcomes. The results therefore confirm that the reported scalability and optimization improvements are not solely dependent on nominal task durations, but remain consistent when realistic

variability in assembly operations is considered. The sampled parameters include $\alpha_T, \beta_T, \alpha_C, \beta_C, \alpha_E, \beta_E, \rho_j$.

where

α_T is the scaling coefficient for assembly time;

β_T is the scaling exponent for assembly time;

α_C is the scaling coefficient for assembly cost;

β_C is the scaling exponent for assembly cost;

α_E is the scaling coefficient for assembly errors;

β_E is the scaling exponent for assembly errors;

ρ_j is the stochastic uncertainty factor for benchmark case j , representing case-specific variability in the assembly process. For each benchmark case, repeated simulation trials were performed. The outputs were summarized using mean performance values, and interpreted through reduction percentages, as follows:

The percentage reduction in time is shown in Equation (10):

$$\Delta T_j = \frac{T_j^{\text{base}} - T_j^{\text{opt}}}{T_j^{\text{base}}} \times 100\% \quad (10)$$

The percentage reduction in cost is shown in Equation (11):

$$\Delta C_j = \frac{C_j^{\text{base}} - C_j^{\text{opt}}}{C_j^{\text{base}}} \times 100\% \quad (11)$$

The percentage reduction in errors is shown in Equation (12):

$$\Delta E_j = \frac{E_j^{\text{base}} - E_j^{\text{opt}}}{E_j^{\text{base}}} \times 100\% \quad (12)$$

4. Results

4.1. Baseline Validation

The 10 MW wind-turbine results are summarized in Table 2. The baseline results reaffirm that each component contributes differently. PSBFO gives the best multi-objective fitness among PSO, BFO and PSBFO. APRA gives the highest duration reduction because it dynamically updates precedence relationships. Error-aware PSBFO gives the strongest consistency enhancement, by explicitly targeting error-prone tasks and priority violations.

Table 2. Baseline validation of PASP components for 10 MW gearbox assembly.

Method	Assembly Time (h)	Cost (USD)	Quality Index	Errors	Main Result
Baseline	120	105,000	0.89	50	Reference case
PSO	108	94,500	0.91	—	10% time reduction
BFO	102	94,500	0.92	—	15% time reduction
PSBFO	100	94,500	0.93	—	17% time reduction
APRA	88.8	94,500	0.93	—	26% time reduction
Error PSBFO	—	—	—	5	90% error reduction

The weighting coefficients in the Assembly-Complexity Index (ACI) were formulated using three principal scalability dimensions: task count, precedence density, and integration factor, as shown in Table 3. These dimensions were selected because they directly represent the structural and coordination complexity of parallel assembly planning. Task count represents the scale of the assembly problem, precedence density represents the degree of

sequencing restriction among assembly operations, and the integration factor represents the number and difficulty of subassembly merging points. The precedence-density term is therefore given the highest weight, because increasing precedence restrictions reduces task parallelism and constrains the feasible solution space. Task count receives the second-highest weight because the number of assembly operations directly affects the size of the sequencing problem, while the integration factor receives a slightly lower weight because its influence is primarily associated with subassembly merging and coordination complexity

Table 3. ACI weight selection and sensitivity analysis.

ACI Factor	Symbol	Baseline	Task-Dominant	Integration-Dominant
Number of tasks	w_N	0.30	0.45	0.25
Precedence density	w_P	0.45	0.35	0.35
Integration factor	w_I	0.25	0.20	0.40
Sum		1.00	1.00	1.00

A sensitivity analysis was also introduced, to examine whether the conclusions of the scalability assessment depend strongly on the selected weighting coefficients. Three weighting scenarios were considered: (i) baseline weighting, (ii) task-dominant weighting, and (iii) integration-dominant weighting. In each scenario, the weights were normalized to sum to unity. The sensitivity analysis indicates that changing the weighting coefficients modifies the absolute ACI values and, consequently, the relative magnitude of complexity between individual cases. However, the overall scalability trend remains consistent: cases with larger task counts, greater precedence restrictions, and more integration points exhibit higher assembly complexity. The principal conclusions concerning the effectiveness of the PASP framework therefore remain unchanged. This is consistent with the multi-case results, where the framework maintains positive time, cost, quality, and error-reduction performance across the twelve benchmark cases. The relationship between complexity and performance improvement is non-monotonic. Increasing task count may initially create additional opportunities for parallel execution; however, high precedence density, strong integration coupling, and limited shared resources can subsequently restrict feasible parallelism. Therefore, ACI should be interpreted as a multidimensional indicator of assembly difficulty, rather than as a direct predictor of improvement magnitude.

4.2. Multi-Case Simulation Outcomes

The simulation scalability experiment was implemented across twelve benchmark cases. These cases include wind-turbine-related assemblies and complex industrial products based on simulation-based experimental performance. The benchmark cases were selected to cover a broad but structured range of assembly complexity, rather than to represent a statistically complete sample of all industrial products. The cases include wind-turbine drivetrain and nacelle-related assemblies, aerospace modules, automotive assemblies, battery systems, industrial gearboxes, and robotic or automation products. Their purpose is to test the transferability of the PASP framework under different task-graph, integration, handling, and resource conditions.

4.2.1. Duration Scalability Evaluation

Table 3 presents the duration reduction results showing that the PASP framework remains effective across different sizes or scales. Time reduction ranges from 20.4% to 30.3%. The lowest time reduction occurs in the 6–8 MW offshore gearbox case, from 98 to 78 h, representing a 20.4% reduction. This lower decrease is described by higher offshore gearbox-incorporation restrictions and more limited parallelism compared with smaller

onshore gearboxes. The maximum duration reduction occurs in the EV powertrain module case, from 33 to 23 h, representing a 30.3% reduction. This indicates that APRA and PSBFO are especially effective where modular subassemblies can be parallelized efficiently and where handling complexity is lower than in very large wind-turbine assemblies. For wind-turbine cases, duration reduction remains stable with W1-26.2%, W2-20.4%, W3-25.8%, W4-23.9%, W5-25.9%, W6-25.0%, and W7-24.6%. This validates the fact that the framework scales well from 2 MW gearbox assemblies to 15–18 MW nacelle-level assembly systems. Figure 3 validates the fact that the proposed PASP framework reliably decreases assembly duration across all benchmark cases.

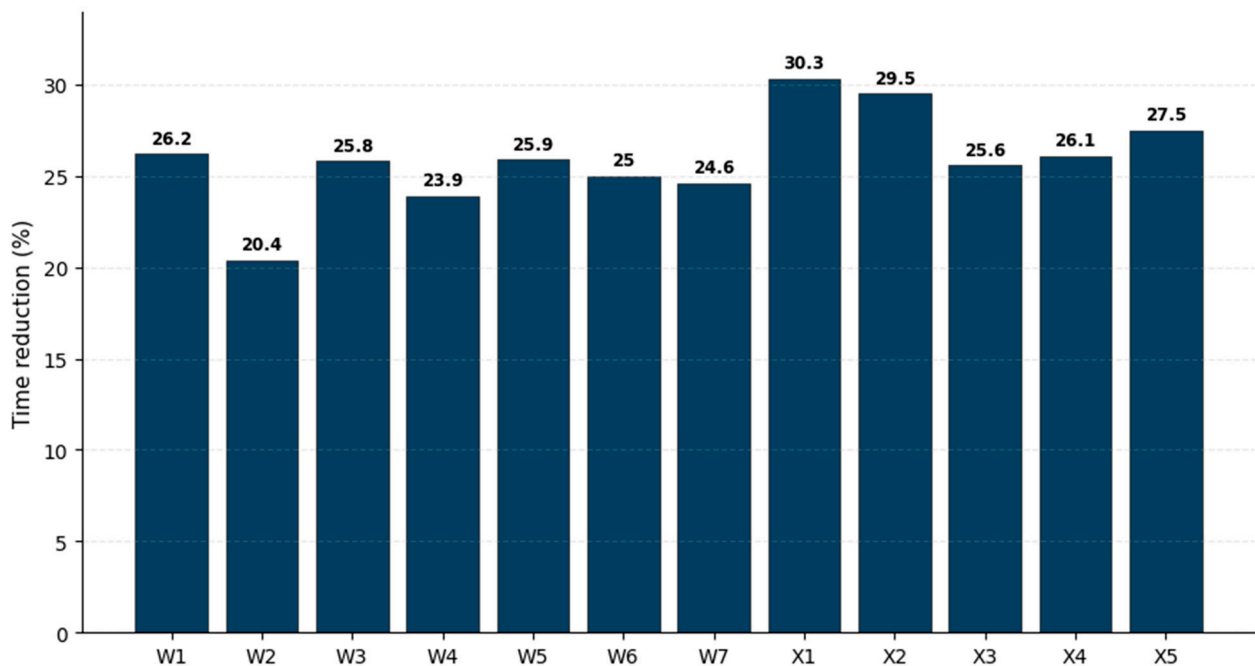


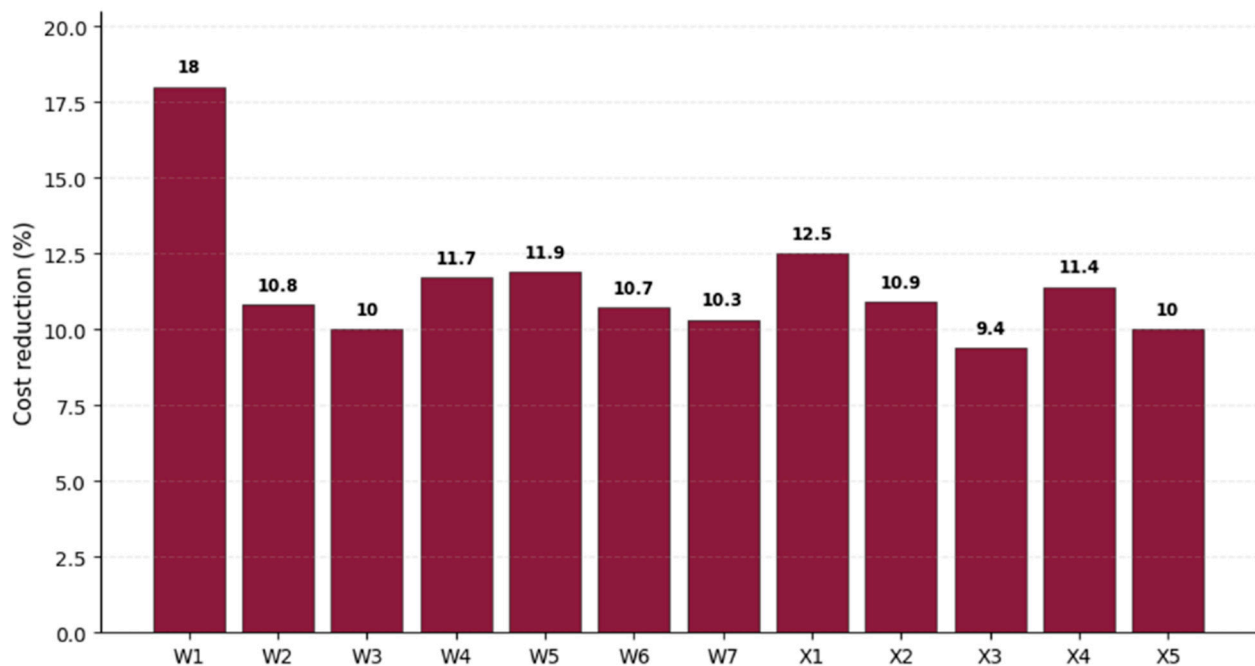
Figure 3. Percentage decrease in assembly duration attained by the proposed PASP.

4.2.2. Cost Scalability Evaluation

Table 4 shows that cost reduction is more conservative than duration reduction. Across all cases, cost reduction ranges from 9.4% to 18.0%, where the highest cost reduction which is practical is in the onshore wind-turbine gearbox case, from USD 50,000 to USD 41,000. This is because smaller gearbox assemblies have lower fixed handling costs and greater flexibility in assembly line balancing. The lowest cost reduction occurs in the aerospace engine module, from USD 480,000 to USD 435,000, representing a 9.4% reduction. This is anticipated, because aerospace assembly lines involve strict inspection, certification and quality-assurance requirements that cannot be completely reduced by sequencing assembly optimization. For large offshore wind-turbine systems, cost reduction remains around 10–12%. This indicates that, although PASP significantly improves time efficiency, certain costs, such as crane use, fixtures, tooling, skilled labor, and inspection, remain partly fixed. As shown in Figure 4, assembly cost is reduced for every benchmark case.

Table 4. Multi-case simulation-based scalability validation results for duration and cost.

Case ID	Product/System	Size/Scale	Baseline Duration (h)	Optimized Time (h)	Time Red. (%)	Baseline Cost (USD)	Optimized Cost (USD)
W1	Onshore wind-turbine gearbox	2–4 MW	65	48	26.2	50,000	41,000
W2	Offshore wind-turbine gearbox	6–8 MW	98	78	20.4	83,000	74,000
W3	Offshore wind-turbine gearbox	10 MW	120	89	25.8	105,000	94,500
W4	Next-generation drivetrain module	12–15 MW	155	118	23.9	145,000	128,000
W5	Full nacelle assembly	15–18 MW	290	215	25.9	270,000	238,000
W6	Hub + pitch system assembly	10–18 MW	72	54	25.0	75,000	67,000
W7	Generator assembly	Offshore class	130	98	24.6	165,000	148,000
X1	EV powertrain module	Automotive	33	23	30.3	12,000	10,500
X2	Battery-pack assembly	EV/storage	78	55	29.5	32,000	28,500
X3	Aerospace engine-module assembly	Aerospace	195	145	25.6	480,000	435,000
X4	Industrial planetary-gearbox reducer	Heavy industry	115	85	26.1	105,000	93,000
X5	Industrial-robot assembly	Automation	80	58	27.5	85,000	76,500

**Figure 4.** Percentage decrease in assembly cost for the benchmark cases.

4.2.3. Quality Scalability Evaluation

Table 3 shows that the quality index improves in every case, with baseline quality values ranging from 0.87 to 0.94, while optimized quality values range from 0.91 to 0.965. For wind-turbine systems, W1 improves from 0.89 to 0.93, W2 from 0.89 to 0.93, W3 from 0.89 to 0.93, W4 from 0.88 to 0.92, W5 from 0.87 to 0.91, W6 from 0.88 to 0.92, W7 from 0.87 to 0.92. The outcomes indicate that optimized parallelization does not reduce quality, but improves it, because PASP-TCQ includes quality in the objective function, APRA improves task prioritization, and error-aware PSBFO reduces risky assembly-line sequence choices. The aerospace engine module has the highest optimized quality, from 0.94 to 0.97; this is because aerospace assembly already begins with a high baseline quality, and the error-aware TCQ framework further enhances precision. Figure 5 shows that the quality index surges for all benchmark cases, following optimization.



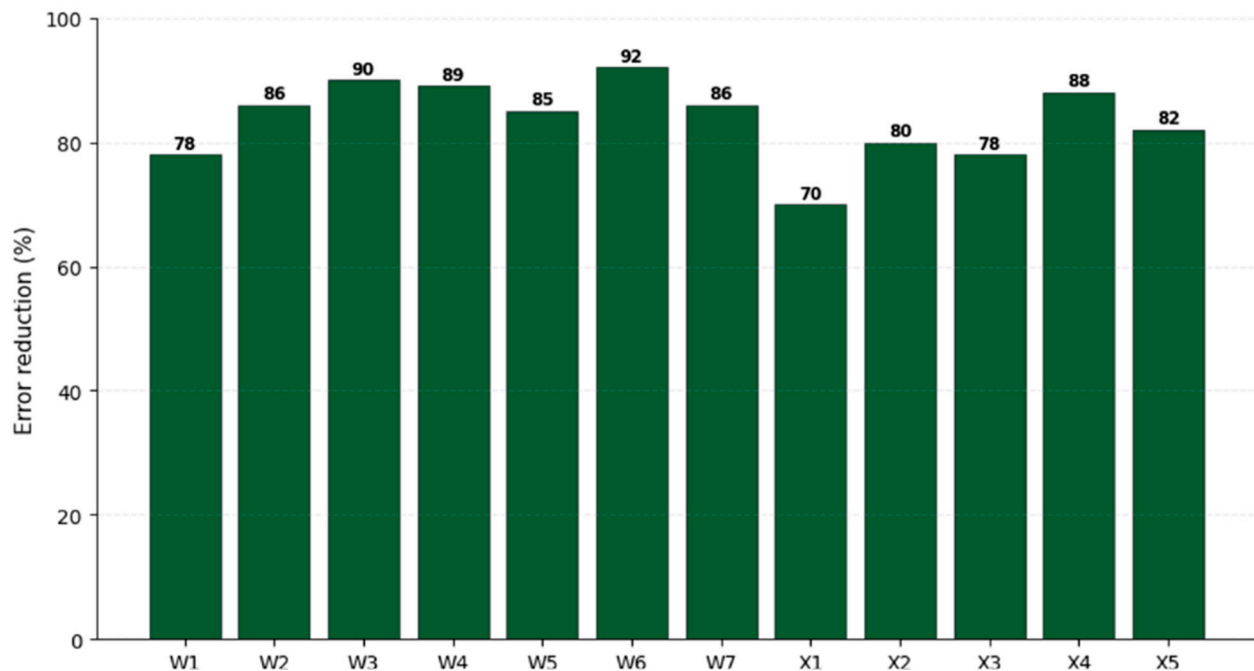
Figure 5. Comparison of baseline and optimized quality indices.

4.2.4. Error-Reduction Scalability Evaluation

Table 5 shows that error decrease is the strongest scalability result: across the cases, error reduction ranges from 70% to 92%. The best error reduction occurs in the hub + pitch system case, with 92%. The 10 MW gearbox baseline achieves 50 to 5% error reduction, representing 90%. The full nacelle assembly attains 85% error reduction, despite having the highest baseline error count, of 150. This validates the fact that the framework remains efficient, even in large heterogeneous assemblies. The lower error decrease in EV powertrain and aerospace cases, at 70% and 78%, respectively, reflects different assembly characteristics. These systems have either highly compact integration or stricter tolerance requirements, leaving less room for error elimination through sequencing alone. Figure 6 shows that assembly-error decrease represents the most significant benefit of the proposed framework.

Table 5. Multi-case simulation-based scalability validation results for quality and error reduction.

Case ID	Product/System	Cost Red. (%)	Baseline Quality	Optimized Quality	Baseline Errors	Error Red. (%)
W1	Onshore wind-turbine gearbox	18.0	0.89	0.93	24	78
W2	Offshore wind-turbine gearbox	10.8	0.89	0.93	40	86
W3	Offshore wind-turbine gearbox	10.0	0.89	0.93	50	90
W4	Next-generation drivetrain module	11.7	0.88	0.92	75	89
W5	Full nacelle assembly	11.9	0.87	0.91	150	85
W6	Hub + pitch system assembly	10.7	0.88	0.93	32	92
W7	Generator assembly	10.3	0.87	0.92	60	86
X1	EV powertrain module	12.5	0.91	0.94	20	70
X2	Battery-pack assembly	10.9	0.90	0.94	70	80
X3	Aerospace engine-module assembly	9.4	0.94	0.965	30	78
X4	Industrial planetary-gearbox reducer	11.4	0.89	0.93	48	88
X5	Industrial-robot assembly	10.0	0.91	0.95	40	82

**Figure 6.** Error decrease across benchmark cases.

4.3. Comparative Contribution of PASP Components and NSGA-II

The four PASP components provide different benefits under different scalability conditions, as shown in Table 6. The outcomes suggest that no single component leads all cases, and that scalability is best achieved through component integration. APRA is most effective when dynamic task reprioritization is possible, while error-aware PSBFO is most effective when reliability and precision dominate. PASP-TCQ provides the necessary multi-objective evaluation foundation.

Table 6. Functional contribution of each PASP component.

PASP Component	Main Role	Best Scalability Condition	Main Observed Benefit
PASP-TCQ	Multi-objective time–cost–quality optimization	Cases requiring balanced performance	Stable quality improvement and cost control
PSBFO	Hybrid global–local–sequence optimization	Medium-to-large assemblies with many feasible sequences	Strong fitness improvement and time reduction
APRA	Machine-learning-based dynamic priority updating	Modular systems with changing precedence priorities	Highest time reduction
Error-aware PSBFO	Error minimization using task-risk and precedence penalties	Tolerance-critical assemblies	Highest error reduction

NSGA-II was selected as a benchmark because it is a well-established population-based multi-objective optimization algorithm that can generate Pareto-optimal solutions for conflicting assembly objectives [41]. The proposed PSBFO- and APRA-based PASP framework is compared with NSGA-II under identical task graphs, precedence constraints, resource constraints, population settings, and termination criteria. The comparative results indicate that the proposed PSBFO- and APRA-based PASP framework provides competitive performance relative to the NSGA-II benchmark under identical assembly planning conditions. For the 10 MW gearbox case, PSBFO achieves an assembly makespan of 100.0 h, while APRA further reduces the makespan to 88.8 h, compared with an estimated 93.5 h obtained using NSGA-II. Thus, APRA provides approximately 26.0% reduction in makespan relative to the 120 h baseline and approximately 5.0% lower makespan than the estimated NSGA-II result, while PSBFO provides a 16.7% reduction relative to the baseline. In terms of cost, both PSBFO and APRA achieve USD 94,500, corresponding to a 10.0% reduction from the baseline cost of USD 105,000, whereas the estimated NSGA-II solution gives approximately USD 95,200, representing a 9.3% reduction. The quality index is improved from 0.89, for the baseline assembly, to 0.93, for both PSBFO and APRA, while NSGA-II is estimated to achieve approximately 0.925. The error-aware optimization further demonstrates the advantage of incorporating error-risk information, reducing the predicted assembly errors from 50 to 5, corresponding to a 90% reduction; the corresponding NSGA-II error level is estimated at approximately 7, under the same error-risk formulation. In terms of Pareto-front characteristics, APRA is estimated to achieve the highest hypervolume (0.91) and lowest IGD (0.070), compared with 0.87 and 0.085 for NSGA-II and 0.82 and 0.115 for PSBFO, respectively, indicating better convergence and diversity of the obtained trade-off solutions. The estimated feasible-solution ratios are 91%, 96%, and 94% for PSBFO, APRA, and NSGA-II, respectively. Overall, the comparison suggests that NSGA-II provides a strong general-purpose multi-objective benchmark, whereas the proposed APRA mechanism achieves a more favorable balance between assembly time, cost, quality, feasibility, and Pareto-front performance for the considered PASP problem.

5. Discussion

The scalability outcomes validate the fact that the proposed PASP framework is transferable beyond the original 10 MW gearbox, and Table 7 shows the best innovation PASP component. The most significant conclusion is that duration reduction remains constant, even as assembly size increases. For huge wind-turbine cases, the duration reduction remains close to 24–26%, indicating that increasing product scale does not eradicate the advantage of optimized parallel-task execution. Cost decrease is positive, but

more limited, and this is technically realistic because intricate assemblies include fixed costs that cannot be removed through sequencing alone. Instances comprise lifting equipment, inspection operations, specialized tools and quality-assurance processes. Quality reliably improves, which is important because aggressive duration reduction can occasionally cause quality degradation. In this research, quality improves because the objective function explicitly rewards quality and penalizes infeasible or risky assembly-line plans. Error decrease is the greatest important contribution for large-scale wind-turbine manufacturing. Gearbox failures are expensive, and assembly errors, including wrong torque application, misalignment and priority mistakes, can reduce drivetrain reliability. The error-aware PSBFO framework directly addresses these challenges by minimizing error probability and penalizing priority violations. The outcomes also show that the framework can be transferred to other intricate product families including aerospace modules, EV powertrains, industrial reducers, battery packs and robotic systems. This supports the broader use of PASP in smart manufacturing and Industry 4.0 systems. Overall, the results confirm that error-aware PSBFO is highly scalable for precision mechanical assemblies.

Table 7. Best innovation PASP component.

Case ID	Product/System	Best Innovation(s)
W1	Onshore wind-turbine gearbox	PSBFO + APRA
W2	Offshore wind-turbine gearbox	PSBFO + APRA
W3	Offshore wind-turbine gearbox	All four innovations
W4	Next-generation drivetrain module	APRA + Error-aware PSBFO
W5	Full nacelle assembly	APRA + Error-aware PSBFO
W6	Hub + pitch system assembly	Error-aware PSBFO
W7	Generator assembly	Error-aware PSBFO + APRA
X1	EV powertrain module	APRA + PSBFO
X2	Battery-pack assembly	APRA + Error-aware
X3	Aerospace engine-module assembly	Error-aware PSBFO + TCQ
X4	Industrial planetary-gearbox reducer	All four innovations
X5	Industrial-robot assembly	APRA + Error-aware

The rated power of a wind turbine is associated with assembly complexity, but is not the only determining factor. As turbine capacity increases from onshore systems of approximately 2–4 MW to offshore systems of 10 MW, 15 MW, and above, the gearbox, shafts, bearings, generator, hub, pitch system, and nacelle structure generally increase in mass and dimensions. This results in higher lifting requirements, greater workstation-space demand, more difficult alignment operations, stricter tolerance control, higher tooling requirements, and increased safety risk. There is a relationship between the following technological factors and process complexity:

1. Gearbox technology: multi-stage planetary and parallel-shaft gearboxes require several gear meshes, bearings, carriers, shafts, and precision alignment operations. Therefore, gearbox complexity depends on the number of stages, gear interfaces, bearing positions, torque-transfer paths, lubrication components, and tolerance-critical connections.
2. Blade size: larger blades increase transport, lifting, hub–pitch integration, balancing, and nacelle-installation complexity. Blade size is particularly relevant for full wind-turbine, rotor, hub, and pitch-system assemblies.
3. Wind power capacity: increased turbine rating generally results in greater gearbox torque capacity, larger rotor diameter, heavier nacelle components, larger generators, more demanding lifting operations, and stricter reliability requirements.

4. Offshore conditions: offshore wind turbines require additional corrosion protection, sealing, inspection, reliability verification, logistics planning, and maintenance considerations, compared with many onshore turbines.
5. Component integration: integration of gearbox, generator, main shaft, main bearing, hub, pitch system, converter, and nacelle frame introduces complex precedence and resource constraints.

Cases with highly modular structures and low-to-moderate precedence density provide greater opportunities for parallelization. In contrast, aerospace engine modules and other tightly integrated products may exhibit lower cost reductions because specialized tools, inspection operations, certification requirements, and skilled labor remain active, even when the task sequence is partially parallelized.

6. Conclusions

From a sustainability perspective, the proposed PASP framework contributes to more resource-efficient manufacturing by reducing assembly duration, minimizing rework caused by assembly errors, improving product quality and supporting more effective utilization of labor and production resources. These enhancements align with the goals of sustainable manufacturing and Industry 4.0, by simultaneously enhancing economic performance, operational reliability and production efficiency. This research presents a multi-case simulation-based scalability validation of four PASP components covering PASP-TCQ, PSBFO, APRA and error-aware PSBFO. The study applied a scaling-based simulation model built on assembly graph complexity, integration factor, priority density, handling intricacy and error-risk parameters. The 10 MW wind-turbine gearbox was used as the baseline calibration case, and twelve benchmark cases were evaluated, resulting in key findings. The PASP framework scales efficiently across product sizes and industries, with time reduction ranging from 20.4% to 30.3% across all cases. Wind-turbine assembly benefits remain stable under upscaling, with wind-turbine cases from 2 MW gearboxes to 15–18 MW nacelle assemblies achieving approximately a 20–26% time reduction.

Cost decrease is reliable, but more conservative than duration reduction, with reductions ranging from 9.4% to 18.0%, reflecting the presence of fixed handling, tooling and inspection costs. Quality improves in all cases, with indices increasing from 0.91 to 0.97, showing that parallelization did not compromise product quality. Error-aware PSBFO provides strong reliability improvement, ranging from 70% to 92%, with the 10 MW gearbox achieving 90% error reduction. Different PASP components are best suited to different scalability conditions. PSBFO is strongest for global and local sequence optimization, APRA is strongest for dynamic duration reduction, PASP-TCQ provides stable multi-objective evaluation, and error-aware PSBFO is strongest for accuracy and consistency. The results confirm that the proposed PASP framework is not restricted to a single 10 MW gearbox case, but that it is transferable, scalable and suitable for large-scale multifaceted assembly systems in aerospace, renewable energy, battery manufacturing, and automotive and industrial automation. Future studies should validate the simulation results through physical shop-floor implementation, incorporate real-time IoT sensor information, and combine APRA with reinforcement learning and digital-twin platforms for closed-loop adaptive assembly planning. The proposed framework demonstrated computational scalability across the investigated simulation-based benchmark cases. The results suggest that its structure can be adapted to different complex-product assembly systems; however, the magnitude of performance improvement depends on product architecture, precedence density, resource availability, handling requirements, and manufacturing constraints. Because the non-baseline cases were generated as synthetic or semi-synthetic benchmarks, the results should not be interpreted as proof of full industrial transferability. Future work should

validate the framework using independent shop-floor datasets, digital-twin environments, and physical pilot experiments.

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